International Journal for Housing Science and Its Applications
Publish August 6, 2025. Volume 46, Issue 3 Pages 6953-6964

https://doi.org/10.70517/ijhsa463596

# Using Constrained Optimization Algorithms to Solve Landscape Path Planning and Facility Layout Problems in the Design of Public Environments

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**Abstract** In public environment design, landscape path planning and facility layout directly affect spatial function and aesthetic experience. Traditional methods are difficult to realize the optimal configuration in complex environments, which restricts the quality of environmental design. In this study, a landscape path planning and facility layout method based on the Improved Artificial Fish Swarm Optimization Algorithm (MCP-AFSA) for public environments is proposed. The search efficiency and path quality of the traditional artificial fish school algorithm in an obstacle environment are optimized by introducing two-way search and path smoothing strategies. Meanwhile, a public environment facility layout optimization model considering multiple objectives, service supply differentiation, demand precision and spatial condition refinement is constructed. The experimental results show that under the same accuracy requirements, the iteration number of MCP-AFSA algorithm is significantly lower than that of the standard PSO and GA algorithms, e.g., in the multi-peak function test, the minimum value of MCP-AFSA algorithm is infinitely close to 0 after 2,000 iterations, while PSO and GA algorithms stay at about 0.18 and 0.8, respectively. In the 150×150 simulation map, the average path score of the improved algorithm reaches 825.59, which is 9% higher than that of the traditional algorithm's 757.45, and the path smoothing is significantly improved. In addition, in the significance test of public environment design indicators, the mean value of the proposed method is as high as 83.67%, which is much better than the comparison methods based on distance measurement (22.82%) and spatial growth simulation (45.55%). The synthesis shows that the proposed method has high practical value and application prospect in solving landscape path planning and facility layout problems in public environment design.

**Index Terms** Artificial Fish Swarm Algorithm, Landscape Path Planning, Facility Layout Optimization, Bidirectional Search, Path Smoothing Strategy

## I. Introduction

Cities are the products of the high development of human civilization, and they are spaces for living and working [1]. As the process of urbanization has increased the complexity of community space and formed relatively complex behavioral patterns of residents, the importance of public environmental landscape design has become increasingly prominent in this context [2], [3]. Urban public environmental landscape involves a wide range of design content covering many infrastructure and design elements, in the embodiment of local culture at the same time, to achieve the effect of dissemination of urban characteristics, is a business card of the city's image [4]-[6]. Therefore, urban public environmental landscape design has become an important element in shaping the city's image.

Landscape is an important part of the urban development process, in order to ensure the application value of the landscape in the design process, designers should combine the specific landscape, scientific urban public environmental design practice and innovation research, and constantly improve their own design level, so as to improve the practical application of the landscape significance [7]-[9]. Urban public environment landscape design has the practical function of making people's life convenient, which is an important part of material needs [10]. It also has the invisible function of enabling people to improve the cultural and aesthetic level, which is a component of spiritual needs [11]. With the fast-paced development of society, people's spiritual and cultural level has been significantly improved, especially in terms of aesthetics [12], [13]. Therefore, in the process of faster urbanization, the need to take into account the basic functions while combining the city's characteristics of culture and reflecting its aesthetics is a worthy study of today's city image shaping.

As an important part of urban planning and landscape construction, the core task of public environment design is to rationally configure landscape paths and public facilities to provide residents with beautiful, practical and ecologically valuable public space. In the process of modern urban development, the quality of public environment design not only affects the city's image, but also directly relates to the quality of life of residents and the efficiency of urban operation. The landscape path and facility layout planning in public environment is a typical multi-objective optimization problem, which involves the comprehensive consideration of aesthetic value, usage efficiency, ecological protection and economic cost. Traditional planning methods mainly rely on the experience and intuition of designers, and it is difficult to find an optimal solution that satisfies multiple constraints in complex urban environments and lacks scientific quantitative evaluation methods. In recent years, the application of intelligent computing and optimization algorithms in the field of spatial planning has provided new ideas to solve this problem. Among them, bio-inspired algorithms have gradually become an important tool for landscape path planning and facility layout optimization due to their advantages in dealing with multi-objective optimization problems.

Artificial fish schooling algorithm (AFSA), as a kind of population intelligence optimization algorithm simulating fish foraging, schooling and tail chasing behaviors, has the characteristics of strong global search ability, few parameters and insensitivity to initial value, which is suitable for solving complex optimization problems with multiple local optimal solutions. However, when dealing with complex environments with many obstacles, traditional AFSA often generates too many path points, which increases the computational volume and reduces the planning efficiency; at the same time, the resulting paths have too many redundant nodes and inflection points, which affects the effect of practical applications. In addition, the layout of public environmental facilities, as a planning task closely related to landscape paths, needs to consider the attribute differences between facilities, residents' demand preferences and other factors, and the traditional location allocation model is often difficult to meet the requirements of accurate layout. Therefore, how to improve the optimization algorithm to enhance the quality of path planning and construct a more accurate facility layout model has become an urgent problem in the current field of public environment design.

Based on the above problems, this study proposes a path planning and facility layout method for public environmental landscape combined with an improved artificial fish swarm algorithm. First, the path finding efficiency of the artificial fish swarm algorithm in the complex environment is improved by introducing a two-way search strategy; second, the quality of the planned path is optimized by combining the path smoothing strategy; then, the optimization model for the layout of the public environment facilities that takes into account the multiple objectives, differentiation of the service supply, precision of the demand, and refinement of the spatial conditions is constructed; and lastly, the three-dimensional scene is constructed based on the real topographic data to realize the landscape Finally, a three-dimensional scene is constructed based on real terrain data to realize the landscape pattern determination and overall planning. A variety of test functions and simulation experiments are used to verify the effectiveness of the proposed method, which provides new technical support for public environment design. The implementation of this study not only improves the scientificity and rationality of landscape path planning and facility layout, but also promotes the development of public environment design in the direction of refinement and intelligence, which has important theoretical value and practical significance.

# II. Landscape path planning and design method based on artificial fish population optimization algorithm

## *II. A. Artificial fish population optimization algorithm for movement path planning*

### II. A. 1) Basic behavior of artificial fish schooling algorithms

The individual state of an artificial fish can be represented by vector $X=(x_1,x_2,\cdots,x_n)$, while $x_i(i=1,2,\cdots,n)$ is a certain artificial fish at the time of path searching, and the population size of the artificial fish is $N$; the food concentration at the current location of the artificial fish can be represented as $Y=f(x)$; $\delta$ is the crowding factor; $Trynum$ is the maximum number of attempts of the movement of the artificial fish; $t$ is the number of iterations; $Visual$ is the visual range; $Step$ is the step length of the movement of the artificial fish; and $Rand(0,1)$ is the random number of $(0,1)$. Artificial fish find a suitable location according to the requirements of their corresponding food through four behaviors: foraging behavior, swarming behavior, tail chasing behavior, and random behavior.

(1) Foraging behavior

This is an activity by which fish search for food, through which they move in the direction of more food. Let vector $X_i$ be the current state of the artificial fish, $X_j$ is a randomly selected state within the field of view of vector $X_i$, and $X_i(t+1)$ is the positional state of $X_i(t)$ at the next iteration. If $Y_i<Y_j$, indicating that the food concentration is higher in the direction of $X_j$ then the artificial fish moves one unit step to $X_j$ through equation (1), if $Y_i>Y_j$ then it needs to re-select a random state $X_j$ within the field of view of $X_i$ and re-judge the relationship between the food concentration of $X_i$ and $X_j$. If the number of repetitions equals $Trynum$ still does not satisfy the condition, then move one unit step randomly through equation (2). In summary, the foraging behavior can be expressed as:

$$X_i(t+1)=X_i(t)+\frac{X_j(t)-X_i(t)}{\left\|X_j(t)-X_i(t)\right\|}\times Step\times Rand(0,1) \tag{1}$$

$$X_i(t+1)=X_i(t)+Visual\times Rand(0,1) \tag{2}$$

(2) Clustering behavior

Set the number of artificial fish $NF$ in the neighborhood of current artificial fish $X_i$ and its center position $X_c$, if $\delta Y_i < Y_c / NF$ then it indicates that the center of artificial fish in the neighborhood is less crowded and the food concentration is relatively high, then move one unit step to $X_c$ by equation (3), otherwise perform foraging behavior. Namely:

$$X_i(t+1)=X_i(t)+\frac{X_c(t)-X_i(t)}{\left\|X_c(t)-X_i(t)\right\|}\times Step\times Rand(0,1) \tag{3}$$

(3) Tail chasing behavior

When one or several fish in the school find food, they will cause the fish around them to chase their tails. Let the current artificial fish $X_i$ has $N_F$ artificial fish in its field of view, and $X_j$ is the artificial fish with the optimal state within the field of view, if $Y_j / NF > \delta Y_i$, then move one unit step towards $X_j$ through equation (4), otherwise perform the foraging behavior. I.e:

$$X_i(t+1)=X_i(t)+\frac{X_j(t)-X_i(t)}{\left\|X_j(t)-X_i(t)\right\|}\times Step\times Rand(0,1) \tag{4}$$

(4) Random behavior

When the fish does not find a more optimal position by the above 3 behaviors, it will move to a randomly selected position within its current field of view according to equation (2).

**II. A. 2) Artificial fish schooling algorithms in a raster environment**

The basic definitions associated with the grid method are as follows:

Definition 1 A resident cannot cross or collide with an obstacle during the resident's process, and the resident moves one unit step $(Step)$ range is $1 \le Step \le \sqrt{2}$.

Definition 2 The distance between two neighboring grids $d(g_i, g_j)$ formula can be expressed as:

$$d(g_i,g_j)=\sqrt{(X_i-X_g)^2+(Y_i-Y_g)^2} \tag{5}$$

Definition 3 Let the position of the artificial fish at a certain moment be $P(X_i, Y_i)$ and the position of the target node be $P(X_j, Y_j)$, then the food concentration function $H$ is shown in equation (6). Path Planning Optimization Criteria The path with the shortest distance is the optimal path, and through equation (6), it can be seen that this paper takes low food concentration as the criterion for path optimization. That is:

$$H=\sqrt{(X_j-X_i)^2+(Y_j-Y_i)^2} \tag{6}$$

Definition 4 $\delta$ is the crowding factor with a range of $(0,1)$.

Definition 5 The field of view of the artificial fish $Visual_{g_i}=\{g|\ g\in S, d(g,gi)<R\}$, $R$ is the radius of the field of view, and $S$ denotes the entire region.

Definition 6 When choosing a random position for the next moment, the artificial fish can only choose within the feasible domain $allow\_area$ $allow\_area \in \left\{P_i \le \left\|P_i-P_f\right\| \le 2, P_i, P_f \in Allow, P_i, P_f \notin Barrier\right\}$, $P_f$ is the position in the feasible domain, $Allow$ is the feasible domain for the movement of the inhabitants, and $Barrier$ is the obstacle region.

**II. A. 3) Optimization of the artificial fish schooling algorithm**

Traditional artificial fish swarm algorithm [14], [15] when the obstacles are more will make the algorithm in the search path to find too many path points, which leads to the algorithm of these path points are to judge and save the algorithm to increase the amount of computation to reduce the efficiency of the path planning, in order to address this problem this paper proposes a bidirectional fish swarm algorithm. And for the retrieved path there are redundant nodes and inflection points more problems, proposed a two-way artificial fish swarm optimization algorithm combined with path smoothing strategy.

(1) Bidirectional Artificial Fish Swarm Algorithm

Bidirectional artificial fish swarm algorithm in the path search process will appear some special circumstances, this paper proposed bidirectional artificial fish swarm using positive and negative alternating search strategy to ensure that the positive direction and the opposite direction of the expansion of the node encounter. According to the bidirectional artificial fish school path search steps, the path search process of bidirectional artificial fish school algorithm is shown in Figure 1.

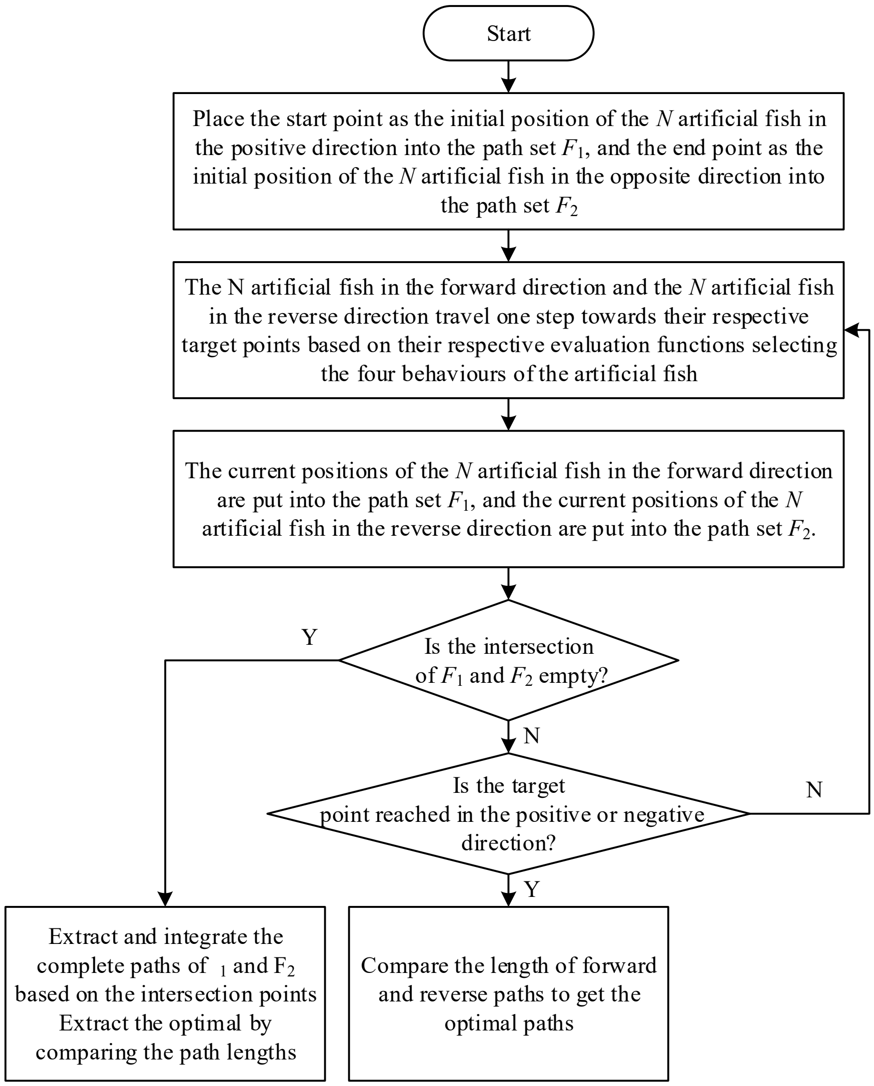


Figure 1: Two-way artificial fish group path search flow chart

(2) Bidirectional artificial fish swarm optimization algorithm introducing path smoothing strategy

The principle of the smoothing strategy is that the line between two nodes cannot touch the obstacles and at the same time cannot cross the obstacles. Through the linear equation can be derived from the map of the horizontal coordinates in the range of $(X_0, X_n)$ all the points on the line, in order to determine whether these points belong to the obstacle area. That is:

$$K = \frac{(Y_n - Y_0)}{(X_n - X_0)}, Y = K(X - X_n) + Y_n \tag{7}$$

If there are points belonging to the obstacle region then the principle of smoothing strategy is violated i.e. the current node $P_0$ and the end point $P_n$ can not be smoothed, then the current node $P_0$ and points adjacent to the end point $P_{n-1}$ are smoothed until the current node and $P_i$ with can be smoothed, where $i$ takes the value range of $[2,n]$. If there is no point between the two nodes of the smoothing process that are in the region of the obstacle nodes are deleted between the current node $P_0$ and the end point $P_n$ All nodes. The new improved artificial fish schooling algorithm (MCP-AFSA) is finally formed.

### *II. B.* ***Regional landscape planning methodology design***

The object of regional landscape planning is the entire regional landscape system, and the scope of planning is to focus on the regional landscape system and cover a wide range of areas that are closely related to and have a greater impact on the development of the regional landscape as a whole. It will combine the actual situation of ecology and humanities in the study area, apply modern technology to identify the key landscape resources in the region, combine multiple theories such as hierarchical analysis method, urban disaster science and urban planning, plan for ecological construction, and reflect the construction effect of part of the ecological sub-area and the main ecological project through technical means. According to this principle, the technical route of regional landscape planning is formulated, and the working procedure of regional landscape planning is shown in Figure 2.

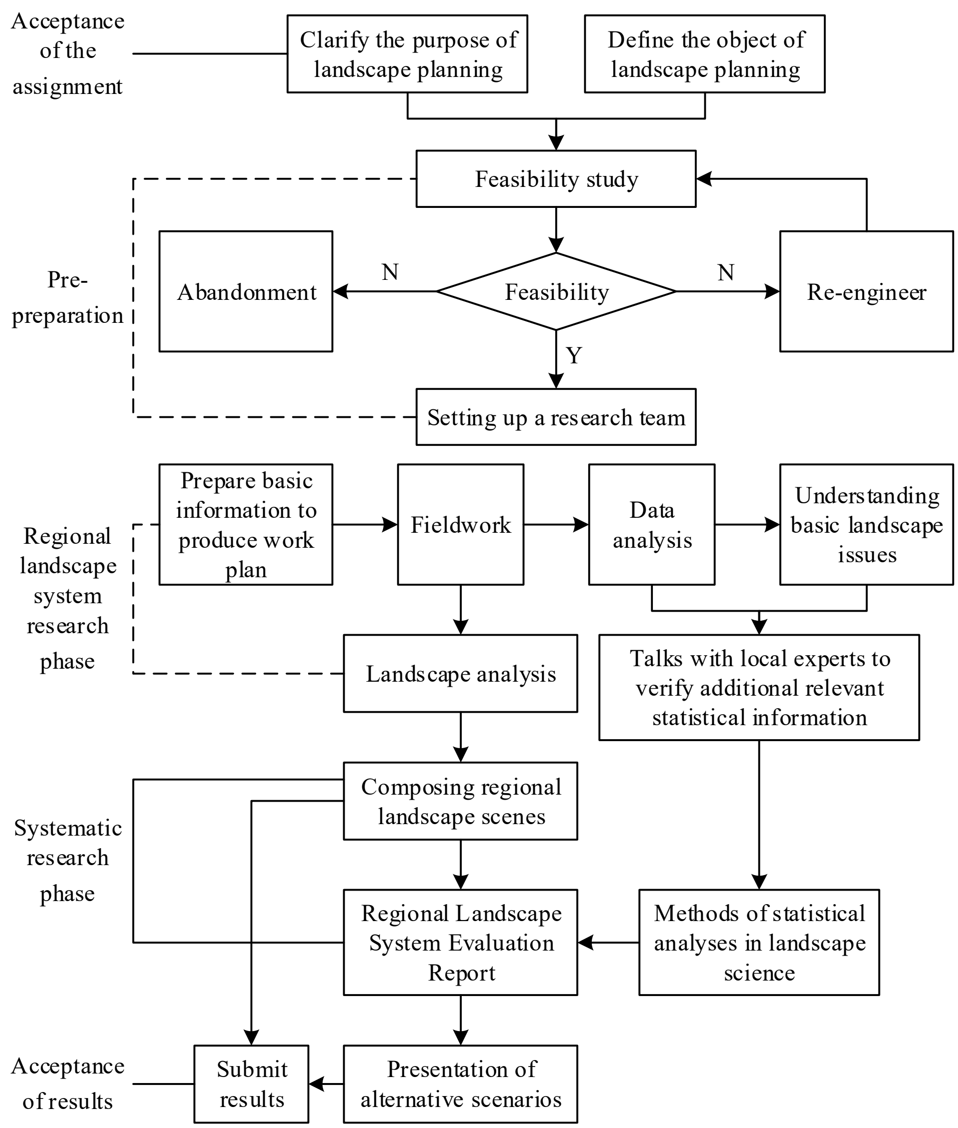


Figure 2: Regional landscape planning work chart

#### **II. B. 1) Constructing a regional 3D scene**

Inclined photogrammetry is applied to acquire ground image data from different angles at the same time by carrying cameras with different angles. The covariance equation in the digital photogrammetric system is the basis for establishing the relationship between the image-square coordinate system and the object-square coordinate system, according to which the covariance equation can be derived to solve the photogrammetric data, and the covariance equation formula is:

$$\begin{cases} x = -f\dfrac{a_1(X-X_s)+b_1(Y-Y_s)+c_1(Z-Z_s)}{a_3(X-X_s)+b_3(Y-Y_s)+c_3(Z-Z_s)} \\ y = -f\dfrac{a_2(X-X_s)+b_2(Y-Y_s)+c_2(Z-Z_s)}{a_3(X-X_s)+b_3(Y-Y_s)+c_3(Z-Z_s)} \end{cases} \tag{8}$$

where, $a_i$ , $b_i$ and $c_i$ are constant coefficients, and $X$ , $Y$ , $Z$ , $X_s$ , $Y_s$ and $Z_s$ are the actual area coordinates and image area coordinates, respectively. The planning and design of the regional landscape is mainly accomplished by establishing a three-dimensional solid model of the region.

Let $m$ and $n$ denote the length of the grid in $X$ and $Y$ directions respectively, then $i = int(X/n)$ and $j = int(Y/n)$, where $int$ denotes the rounding operation. Set point $(X,Y)$ falls in point $(i,j)$, point $(i+1,j)$, point $(i+1,j+1)$ and point $(i,j+1)$ in the four-point grid, according to the elevation value of the above grid and the position of point $P(X,Y)$, the elevation value of point $P(X,Y)$ can be calculated $Z$. such as the grid of four points of the spatial coordinates of the shorthand of $d_1(X_i,Y_j,Z_{ij})$ , $d_2(X_{i+1},Y_j,Z_{i+1,j})$ , $d_3(X_i,Y_{j+1},Z_{i,j+1})$ , $d_4(X_{i+1},Y_{j+1},Z_{i+1,j+1})$ , then point $P_1$ of the elevation of $Z_1 = \lambda_1 Z_{ij} + (1-\lambda_1)Z_{i+1,j}$ , point $P_2$ of the elevation of $Z_2 = \lambda_1 Z_{i,j+1} + (1-\lambda_1)Z_{i+1,j+1}$ , and $\lambda_2 = (Y-Y_j)/(Y_{j+1}-Y_j)$ can be known from the elevation of point $P$ is $Z = \lambda_2 Z_1 + (1-\lambda_2)Z_2$. based on the above construction of the three-dimensional scene. Realize the design of regional landscape planning method. First of all, through the digital elevation model of the required elevation data, to get the mathematical model of regional division is:

$$p(\omega_k) = p\left(u_k, \Sigma_k\right) y_o \tag{9}$$

where, $u_k$ denotes the parameter node of zoning and $\Sigma_k$ denotes the data feature set. When planning regional landscapes, key elevation data are first extracted from existing paper and digital terrain data, which are usually expressed in two forms: contour lines and elevation points. To construct an accurate terrain model, these two data formats are combined using advanced tools in the ArcGIS 3D spatial analysis module. Through this process, an irregular triangular network (TIN) is generated, which is the basis for constructing a digital elevation model (DEM).

Next, the elevation data triangulation network [16] was converted, reasonable resolution information was set, the required DEM data were obtained, and the preparatory data were fused with the processed DEM data and the measured image data. A digitized terrain file is obtained, which records in detail the undulations, changes, and characteristics of the terrain in the region. Finally, based on the digitized terrain file, the information of regional roads, water systems, buildings, vegetation and other ancillary elements are integrated. Through this comprehensive application of multiple elements, a 3D scene with a strong sense of reality and rich details is successfully constructed to provide an intuitive and powerful support for subsequent landscape planning and design.

#### II. B. 2) Defining regional landscape patterns

Landscape structure design is the further implementation of the regional functional plan. The three elements of landscape structure are patch, matrix and corridor. Through the reasonable configuration of landscape elements, the three elements are organically combined so that they can respectively undertake the functions of ecological environment cultivation, ecological balance maintenance, ecological information storage, transmission and aggregation and dispersion, so as to plan and design the landscape spatial structure. Choose the landscape pattern suitable for the planning area according to the terrain type.

#### II. B. 3) Realization of the regional landscape plan

On the basis of determining the regional landscape pattern, the planning results of the regional landscape are derived by combining the constituent elements of the regional landscape. Figure 3 represents the composition system of the regional landscape.

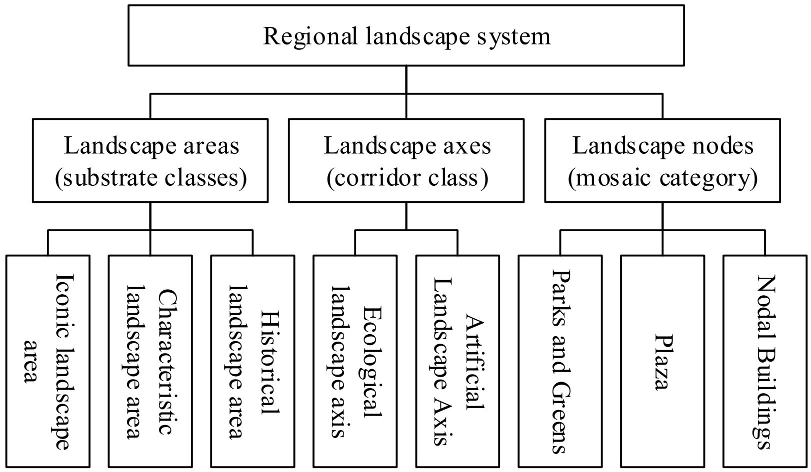


Figure 3: Landscape architecture

### *II. C. Landscape path planning and facility layout system for the public environment*

#### II. C. 1) Modeling the problem of optimizing the layout of public environmental facilities

The location allocation model [17] is the most effective method to solve complex facility layout problems with multi-objective optimization and multi-conditional constraints. Precise public environmental facility allocation requires further consideration of factors such as attribute differences among facilities and residents' demand preferences when constructing the layout optimization model. This section proposes the improvement ideas of the public service facility layout optimization model from four aspects, namely, diversification of facility planning objectives, differentiation of facility service supply, precision of residents' service demand, and refinement of layout spatial conditions, and points out the relevant application scenarios.

(1) In terms of optimization objectives:

The precise layout optimization model needs to establish a multi-objective system and comprehensively consider the multi-dimensional benefits of facility layout. When there are contradictions and conflicts in the goal orientation of planning, the multi-objective optimization model can seek to find a suitable layout scheme through the compromise processing of multiple objective functions. A specific multi-objective algorithm is used to find the approximate optimal solution of the model, from which a satisfactory solution is selected according to the decision-making preference, which is suitable for decision-making scenarios where there is a lack of sufficient information to support the optimization of the objective ordering or weight allocation.

(2) In terms of service provision:

Layout optimization models oriented to different types and grades of facilities need to differentiate the expression of the service capacity of the facilities in order to improve the precision of the results of facility resource allocation. The service contents of facilities of different grades overlap, but there are significant differences in service level and service capacity, etc. Layout optimization should not only achieve quantity balance, but also ensure quality balance.

(3) In terms of service demand:

The principle of gravity simulates the probabilistic access of residents to facilities, which is an important form of improvement of the layout optimization model. And with the help of multi-source spatio-temporal big data to analyze the behavioral activity law of residents, to obtain the facility use characteristics of different individuals and groups, to accurately estimate the spatio-temporal service demand of residents and convert it into model parameters is the core content of the precise improvement of layout optimization model.

(4) Layout spatial conditions:

The precise layout optimization model needs to further improve the spatial modeling capability and comprehensively consider the influence of spatial environmental factors. Based on spatio-temporal big data and Internet open data, the precise layout optimization model is able to extract the dynamic movement trajectory of residents, simulate dynamic traffic operation, and measure the spatial accessibility of the public environment more accurately and realistically. For specific layout optimization decision-making scenarios, the model construction also needs to consider the constraints of spatial environmental factors such as air quality and height of surrounding buildings.

**II. C. 2) Optimization Model Solution for Public Environmental Facilities Layout**

The process of solving the public environment facility layout model is an iterative process that involves constant trade-offs between abstraction and solvability. Considering too comprehensive and detailed facility layout factors may lead to the model being difficult to solve or even unable to converge. According to the actual performance results of the optimization algorithm, it is sometimes necessary to simplify the model structure or reduce the problem scale by means of dimensionality reduction and lightweighting, so that the layout optimization model can obtain acceptable and stable convergence results within a reasonable time. In terms of dimensionality reduction, there exists a complex superposition substitution between many factors considered in the layout optimization model, and simplifying the model parameters can avoid the situation of premature stagnation or failure of convergence of the model to a certain extent. In addition, the clustering and merging of demand points and facility points can reduce the size of the OD matrix, so that the model can obtain an approximate optimal solution that meets the requirements within a reasonable time range, which is convenient for the model to be promoted and used in actual planning scenarios.

# III. Results of landscape path planning and facility layout in public environmental design

### *III. A. Comparative analysis of experimental simulations of different algorithms*

In this section the experimental simulation tested the performance of MCP-AFSA algorithm using single peak function, multi-peak function, G function, and A function and analyzed it in comparison with algorithm PSO and GA algorithm. Each algorithm is allowed to run independently for many times by finding the minimum value of the four functions and finally the three algorithms are comprehensively analyzed to observe the comparison of the three algorithms on the same function. The following is a comparison between MCP-AFSA algorithm and GA algorithm, standard particle swarm algorithm. The variations of the minimum values on the single-peak function, multi-peak function, G-function and A-function are shown in Figs. 4-7. The results show that the method of this paper is better than the PSO algorithm and GA algorithm in terms of the variation of the minimum value on all four functions. For example, in the multi-peak function, this paper's MCP-AFSA algorithm after 2000 iterations, its minimum value is infinitely close to 0, while the PSO algorithm and algorithm GA algorithm's minimum value changes around 0.18 and 0.8, respectively, which is obvious that this paper's algorithm performs significantly better than the comparison algorithms, and proves that this paper's method is good for simulation.

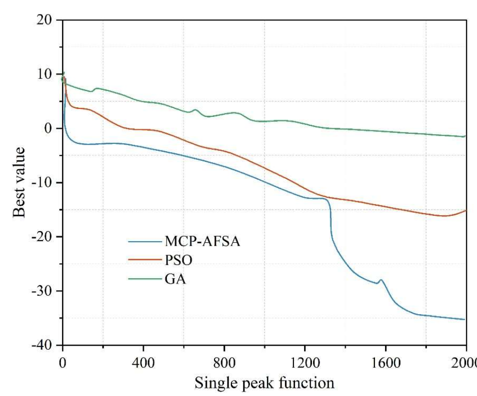


Figure 4: The change in minimum value on a single peak function

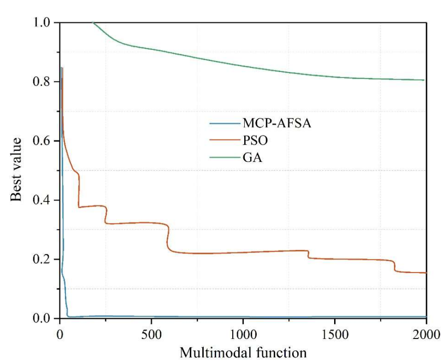


Figure 5: The change in the minimum value on the double peak function

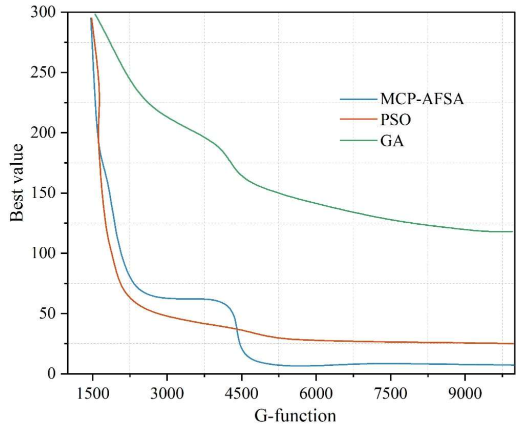


Figure 6: The change in the minimum value on the G-function

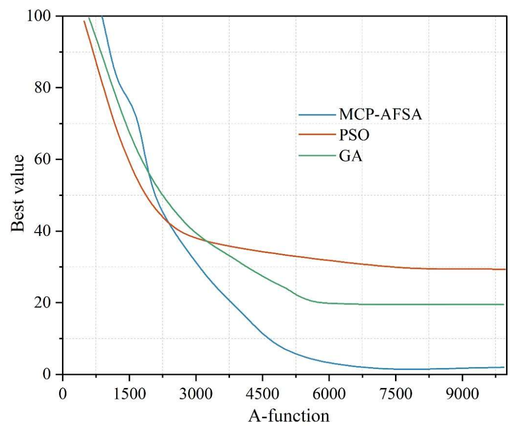


Figure 7: The change in the minimum value on the A-function

To further examine the performance of the MCP-AFSA algorithms, the experimental simulation functions are quantitatively analyzed. In this paper, three accuracies of 0.1%, 1% and 5% are set to test the performance of the three algorithms. The comparison results of the number of iterations under different accuracy requirements are shown in Table 1. As can be seen from the table, the number of iterations of the optimization results of the MCP-AFSA algorithm is significantly lower than those of the standard PSO algorithm and the GA algorithm, which indicates that the optimization ability of the MCP-AFSA algorithm is enhanced relative to the standard PSO algorithm and the GA algorithm, and avoids premature convergence. The simulation test function experiment verifies that the method of this paper is effective.

Table 1: The number of iterations is compared with different accuracy

| Function type | Method | Accuracy | | |
|---|---|---|---|---|
| | | 0.001 | 0.01 | 0.05 |
| Single peak function | GA | 8436 | 4326 | 2437 |
| | PSO | 5954 | 3255 | 1036 |
| | MCP-AFSA | 3659 | 1950 | 849 |
| Multimodal function | GA | 7645 | 4530 | 1583 |
| | PSO | 5957 | 3253 | 939 |
| | MCP-AFSA | 3722 | 1019 | 407 |
| G function | GA | 9473 | 5473 | 4018 |
| | PSO | 7665 | 3554 | 2009 |
| | MCP-AFSA | 4934 | 2633 | 1027 |
| A function | GA | 9058 | 6326 | 4503 |
| | PSO | 21546 | 8958 | 6317 |
| | MCP-AFSA | 7363 | 5631 | 3636 |

### *III. B. Landscape Path Planning Results and Analysis*

In order to verify the effectiveness of the proposed method, this paper uses Matlab software for simulation analysis and sets the maximum number of iterations of the algorithm to be 300, the number of fish population to be 50, the field of view of each fish to be 5, and the updating step size to be 0.5. In the paper, the multi-objective optimization arithmetic is firstly used to verify the effectiveness of the proposed algorithm. That is, there are:

$$f_1(x_1,x_2)=0.5+\frac{\left(\sin\sqrt{x_1^2+x_2^2}\right)^2-0.5}{\left[1+0.001(x_1^2+x_2^2)\right]^2} \tag{10}$$

The above equation has a sinusoidal envelope function with an infinite number of minima. Fig. 8 shows the comparison results of the two algorithms for finding the optimum. As seen from the figure, the improved algorithm proposed in this paper is able to obtain better minima after fewer iterations.

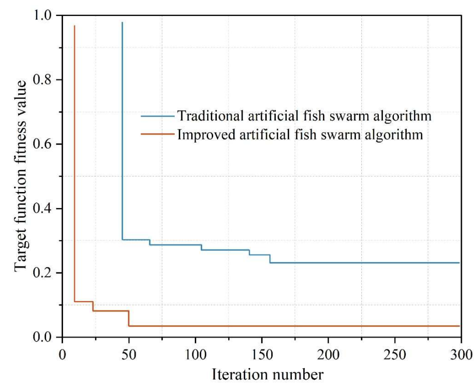


Figure 8: Two algorithms are optimized for comparison

In this paper, the traditional artificial fish school algorithm and the proposed improved algorithm are used to perform 15 calculations in a 150×150 simulation map, and the simulation path planning results obtained by the different algorithms are shown in Fig. 9, in which the irregular graphics represent the scenery in the planning path, and the regular graphics represent the featured landscape. As can be seen from the figure, the proposed algorithm is significantly better than the traditional artificial fish schooling algorithm with higher accuracy and smoothness.

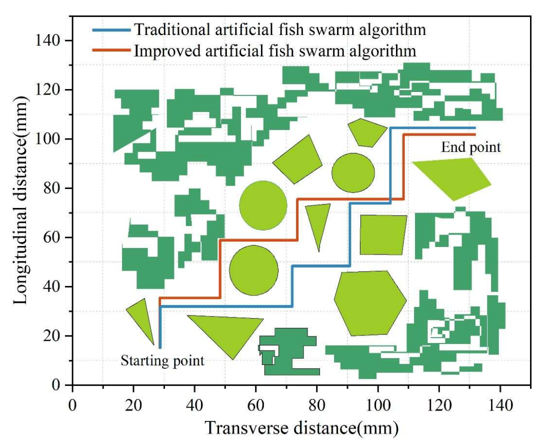


Figure 9: Simulation path results of different algorithms

The comparison results of the solutions before and after the algorithm improvement are shown in Table 2. It can be seen that the improved algorithm proposed in this paper is obviously better than the traditional algorithm, in which before and after the improvement of the algorithm, the difference between its average value and the optimal solution is 86.55 and 18.41, respectively; the number of times to reach the optimal number and the number of times to reach the accuracy are reduced by 11 and 17 times respectively compared with the pre-optimization period, which can be seen that the improved algorithm has a more desirable convergence effect and the ability of local search.

Table 2: The comparison results of the algorithm are improved

| method | Traditional artificial fish swarm algorithm | Improved artificial fish swarm algorithm |
|---|---|---|
| Optimal solution | 844 | 844 |
| Worst solution | 631.59 | 836.14 |
| Mean value | 757.45 | 825.59 |
| The number of times | 37 | 26 |
| The number of times of accuracy | 52 | 35 |

### *III. C. Public infrastructure layout results and analysis*

In order to verify the overall effectiveness of the landscape path planning and facility rational layout methods in the design of public environment, with the help of the experimental platform of this test is Mulan, and the operating system is Windows. respectively, the method of this paper (Method 1), the landscape path facility planning method based on the perspective of distance measurement (Method 2), and the landscape path facility planning and layout method based on the simulation of spatial growth (Method 3) were used for test to compare the significance of the important indicators of landscape path facility planning selected by the three methods.

The indicator significance test results of the three different methods are shown in Figure 10. As can be seen from the analysis, the indicator significance of the rational layout method of landscape path planning facilities in public environment design is above 73.13% in multiple iterations, with a maximum of 96.15%. When tested using the landscape path facility planning method based on distance measurement perspective, the indicator significance in multiple iterations were all below 33.91%, with a minimum of 12.33%. The indicator significance fluctuated within 32.13%-60.89% when tested using the landscape path facility planning and layout method based on spatial growth simulation. Comparing the test results of Methods 1-3, it was found that the mean values of the significance were 83.67%, 45.55%, and 22.82%, respectively, which shows that there is a highly significant difference between this paper's method and the comparison methods.

This proves that the method of this paper in the public environmental design of landscape path planning facilities and rational layout of the selected indicators of high significance, can better solve the landscape path planning and facilities layout, verified the method of this paper layout rationality is higher.

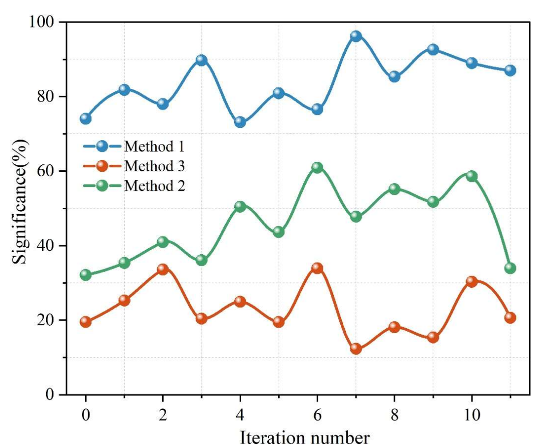


Figure 10: Index significance test results of three different methods

## IV. Conclusion

Aiming at the landscape path planning and facility layout problems in public environment design, this paper proposes a solution based on the Improved Artificial Fish Swarm Optimization Algorithm (MCP-AFSA), and the effectiveness and superiority of the method is proved through multiple experiments. The experiments show that the improved MCP-AFSA algorithm significantly outperforms the traditional PSO and GA algorithms in terms of optimization performance. Under the 0.1% accuracy requirement, the MCP-AFSA algorithm requires only 3722 iterations in the multi-peak function test, while the GA and PSO algorithms require 7645 and 5957 iterations, respectively, and the computational efficiency is improved by about 40%. In terms of path planning quality, the average rating of the paths planned by the MCP-AFSA algorithm reaches 825.59, which is 68.14 points higher than that of the traditional algorithm, and the path smoothness and accuracy are significantly improved. Especially in the complex obstacle environment, the path generated by the improved algorithm has fewer inflection points and enhanced obstacle avoidance capability, which is more in line with the actual landscape planning needs.

In the optimization test of the layout of public environmental facilities, the index significance of this method reaches up to 96.15%, and the average value is 83.67%, which is far more than the comparative methods based on distance measurement and spatial growth simulation. By constructing a layout optimization model that considers multiple objectives, service supply differences, demand precision and spatial conditions, it achieves a reasonable allocation of facility resources and meets the realistic demand of overlapping service contents but different service levels for different levels of facilities.

Overall, the method in this paper successfully solves the synergistic optimization problem of landscape path and facility layout in public environment design, which not only improves the efficiency of the algorithm, but also significantly improves the quality of planning. Future research can further explore the application of multi-source spatio-temporal big data in the analysis of residents' behavior, as well as the optimization of the algorithm adaptability under different terrain conditions, to provide more accurate technical support for the construction of smart cities.

## Funding

This work was funded by the Scientific Research Fund of Bengbu University (Project No. 2024YYX78QD).

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